WATERSHED-SCALE CROP TYPE CLASSIFICATION USING SEASONAL TRENDS IN REMOTE SENSING-DERIVED VEGETATION INDICES

G. S. Jang, K. A. Sudduth, E. J. Sadler, R. N. Lerch

ABSTRACT. *Analysis and simulation of watershed-scale processes requires spatial characterization of land use, including differentiation among crop types. If this crop type information could be obtained accurately from remote sensing data, the effort required would be significantly reduced, especially for large watersheds. The objective of this study was to compare two methods using multiple satellite remote sensing datasets to differentiate land cover, including crop type, for the Salt River/Mark Twain Lake basin in northeast Missouri. Method 1 involved unsupervised classification of Landsat visible and near-infrared satellite images obtained at multiple dates in the growing season, followed by traditional, manual class identification. Method 2, developed in this research, employed the same unsupervised classification but also used normalized difference vegetation index (NDVI) maps obtained on a 16-day cycle from MODIS satellite images as ancillary data to derive seasonal NDVI trends for each class in the classification map. Tree analysis was applied to the NDVI trend data to group similar classes into clusters, and crop type for each cluster was determined from ground-truth data. Additional ground-truth data were used to assess the accuracy of the procedure, and crop acreage estimates were compared to county-level statistics. The overall classification accuracy of Method 2 was 3% higher than that of Method 1. Method 2 was also more efficient in terms of analyst time and ground-truth data requirements. Therefore, this method, employing variations in seasonal NDVI trends, is suggested for differentiation of crop type. The 30-m resolution crop type maps developed using this process will be useful as input data to environmental analysis models.*

Keywords. *Crop classification, Landsat, MODIS, NDVI, Watershed management.*

Knowing the spatial distribution of land cover or land use is important both for understanding the effects of the land cover on the environment and for developing management strategies that can minimize negative environmental impacts. Land use is an important input to the watershed-scale water quality models, such as SWAT (Arnold et al., 1998), that are widely used to assess the effects of conservation measures. The resolution of land use data employed in the SWAT model has typically ranged from 30 m (Bosch et al., 2004) to 250 m (Srinivasan et al., 1998). In the U.S., the National Land-Cover Database (NLCD; Homer et al., 2004) provides this type of information. However, the NLCD does not provide sufficient detail for studying resource issues in agricultural areas because it does not differentiate among crops. Such differentiation is important when assessing the impact of crop management on the environment because different fertilizers and pesticides are applied to different crops. One product that does map different crops is the Cropland Data Layer (CDL) produced annually by the USDA National Agricultural Statistical Service (NASS) (Craig, 2001). However, these maps cover only selected portions of the U.S. Because the methodology used to develop the CDL relies on detailed NASS annual sampling data, which are not generally available outside of the agency, alternative approaches are needed to develop crop type maps for other years and/or locations.

For differentiating among crops, examination of differences in their seasonal growth trends may be useful. Because remote sensing-derived vegetation indices are sensitive to crop type, planting date, crop growth stage, and harvest date, such indices may aid in crop identification. However, images must be obtained at the correct point in the growing season because, at early growth stages, soil background effects will dominate the spectral reflectance. Remote sensing crop identification studies conducted in the late 1970s established that multitemporal satellite data were needed, particularly when both spring (e.g., winter wheat) and summer (e.g., corn, soybean) crops were involved (Bauer, 1985). Multitemporal data can also be important for summer crops; Craig (2001) reported that the optimum time to accurately separate corn from soybeans in the U.S. Corn Belt was about mid-August, but this optimum time varied among crops and locations. A majority of recent satellite-based crop classification projects have relied on multitemporal images (Craig, 2001; Cohen and Shoshany, 2002; Van Niel and McVicar, 2004).

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Several methods for developing crop classifications from remote sensing images have been applied and evaluated. A common approach is to categorize all pixels in an image into themes (i.e., crop type) using either supervised classification (SC) or unsupervised classification (USC). Normally, multispectral data are used to perform the classification, and the spectral pattern for each pixel is used as the numerical basis for categorization (Lillesand et al., 2004). SC requires a robust training set where land cover is known as a precursor to the classification process (Schowengerdt, 1997). Robustness in the training set requires that these data be chosen to span whatever variation may be expected within the area of analysis. For example, if the classes are different crops, and planting dates of those crops vary spatially over a region, then the training data for SC should be chosen to be representative of the entire region. USC, often referred to as clustering, is a better alternative when the training set is limited because USC can define many classes based on natural groupings that are inherent in the data (ERDAS, 1999).

Traditionally, thematic classification of an image involves several steps, including feature extraction, training, and labeling (Schowengerdt, 1997). After the image is clustered in the USC process, the analyst must then supervise the labeling using ground-truth data that has been directly or indirectly surveyed in the study area. Selection of homogeneous training areas is an important consideration in classification accuracy. If the training areas for a specific land cover type are not homogeneous, then the training classes are not spectrally separable, and training area accuracies should not be used as an indication of overall accuracy (Lillesand et al., 2004).

Landsat TM and ETM+ data have been widely used for monitoring natural resources. This practice has continued even after the availability of IKONOS and QuickBird satellite data with better spatial resolution, because spectral and radiometric properties have been found to be more important than spatial resolution for accurate land use/cover classification (Toll, 1985). However, because Landsat scenes are only available every 16 days, it is difficult to obtain multiple cloud-free Landsat images at appropriate times during the growing season for crop classification. Although Landsat has good spatial resolution (30 m), this difficulty with capturing seasonal trends is a limitation to the use of Landsat data for crop classification.

For ground-truth data, both field-surveyed data and high-resolution image data have been used. For example, Bellow and Ozga (1991) used data from the national USDA-NASS June Agricultural Survey (JAS) to identify pixels in a classification image corresponding in location to the JAS fields. The JAS is also a major source of ground-truth data for the NASS CDL (Craig, 2001). Wickham et al. (2004) used National Aerial Photography Program (NAPP) photos, digital orthophoto quarter-quadrangle (DOQQ) images, and high-resolution aerial photographic sources to obtain reference land cover labels for western U.S. land cover data. Van Niel and McVicar (2004) combined aerial photography and landowner surveys to develop a ground-truth dataset.

Meanwhile, global monitoring systems with a high temporal resolution, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), can be a good source of auxiliary data for identifying crop type and other land cover. Because MODIS has a 2-day temporal resolution, it is possible to develop a cloud-free vegetation index (VI) image with minimal atmospheric and sun-surface-sensor angle effects on a 16-day cycle (Holben, 1986). Heute et al. (1999) stated that time series analysis of the MODIS VIs would provide consistent spatial and temporal comparisons of global vegetation conditions to monitor the earth's terrestrial photosynthetic vegetation activity. Lobdell and Asner (2004) used growing-season MODIS data for crop discrimination. In this study, MODIS data were able to capture only half of the variability expressed in Landsat data at the field scale, emphasizing the importance of incorporating the higher-resolution Landsat data for field-scale observation. Doraiswamy et al. (2006) evaluated 250-m resolution MODIS NDVI (normalized difference vegetation index) time-series data for assessing soybean crop area in Brazil, and determined that regional crop classification was possible if the MODIS data were first screened for data anomalies. For a crop classification project in Michigan, Brooks et al. (2006) used MODIS imagery to obtain characteristic phenological growth profiles for the major crop types, and then used Landsat data to verify the MODIS phenology results with a higher spatial resolution. Chang et al. (2007) used MODIS data, coupled with regression tree and statistical analysis, to estimate U.S. corn and soybean areas. They obtained good results compared to state-level NASS data, but with more error compared to county-level NASS data. Wardlow and Egbert (2008) used MODIS NDVI time-series data and a decision tree classifier to create crop type maps for the state of Kansas, with an overall accuracy of 84% for discriminating among summer crops. However, they noted a reduction in accuracy for some portions of the state where cropped areas were not well-represented by the 250-m MODIS resolution.

The overall goal of this research was to create crop type maps for the Salt River basin in northeast Missouri to provide input data for a watershed-scale water quality modeling project. The initial objective, reported here, was to evaluate and compare two different crop type classification methods using data from the 2003 crop year. The first, more traditional, method used unsupervised classification of multiple Landsat images, followed by manual class identification using ground survey data. The second method, developed in this research, used the same Landsat-based classification followed by class identification using MODIS-derived seasonal NDVI trends.

Materials and Methods

Study Area

The study area was the Salt River/Mark Twain Lake basin in northeast Missouri (fig. 1), which encompasses an area of 6,520 km^2 within portions of 12 northeastern Missouri counties. The basin includes all of two 8-digit USGS hydrologic unit codes (HUC 07110005 and HUC 07110006) and a portion of HUC 07110007. Additional details can be found in Lerch et al. (2008). Within the basin, land use is predominately agricultural. Cropland accounts for 44% of the area (Lerch et al., 2008), with the primary crops being soybean, corn, wheat, and grain sorghum. In 2003, the relative coverage area of each of these four crops was 60%, 28%, 8%, and 4%, respectively (USDA-NASS, 2003). Additionally, 33% of the basin is in grassland (Lerch et al., 2008), both for hay and pasture to support beef cattle production and as Conservation Reserve Program (CRP) set-aside acreage.

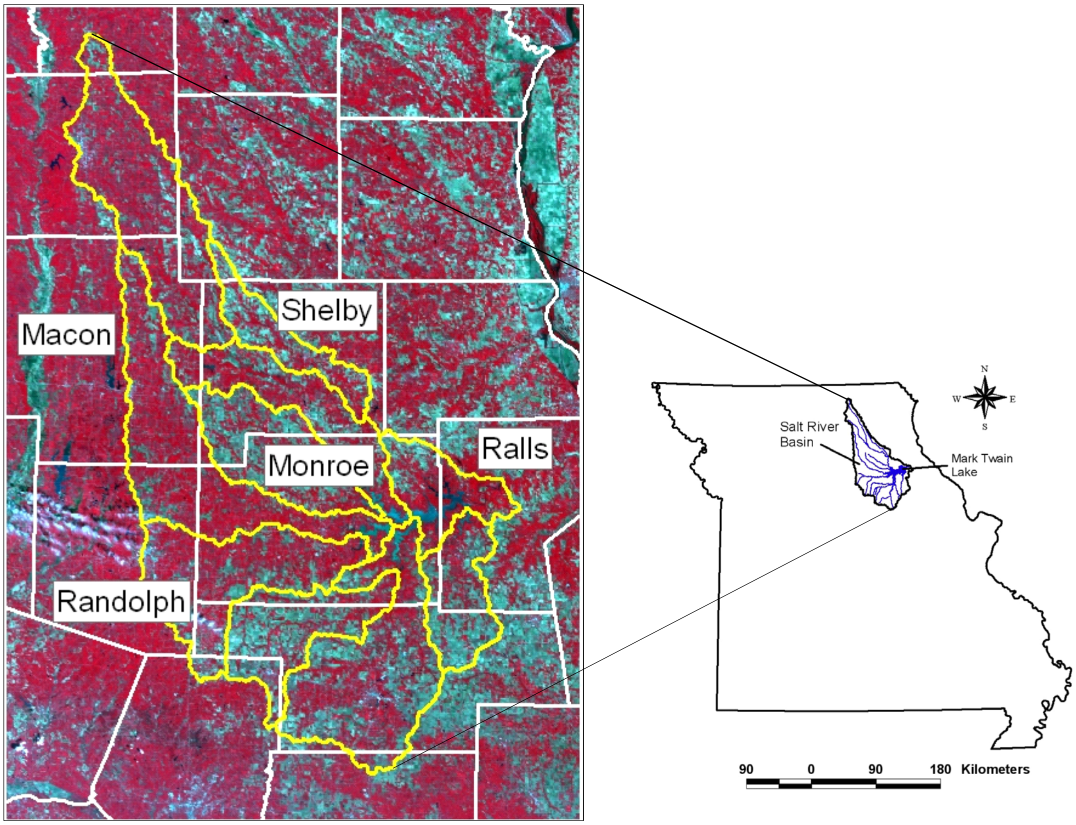

Figure 1. Landsat image (26 May 2003) overlaid with Salt River sub-basin and county boundaries, along with names of counties from which ground-truth data were obtained. Inset shows location of Salt River basin in northeast Missouri.

Mark Twain Lake serves as the public drinking water supply for approximately 42,000 people, and the Salt River basin, which supplies water to the lake, has a well-documented history of herbicide and sediment contamination problems (Lerch and Blanchard, 2003; USDA-NRCS, 2000). The claypan soils that predominate within the basin create a natural barrier to percolation, promoting surface runoff. This results in a high degree of vulnerability to surface transport of sediment, herbicides, and nutrients. Because of the documented soil and water quality problems, the Salt River basin was selected as one of 12 USDA Agricultural Research Service (ARS) benchmark watersheds for the Conservation Effects Assessment Program (CEAP) (Lerch et al., 2008). A key component of CEAP is the use of process-based models to evaluate the effect of agricultural management practices on water quality. Thus, knowledge of the spatial distribution across the watershed of various management practices, including crop type, was needed.

Satellite and Ground-Truth Data

Landsat Images

Nearly cloud-free Landsat 7 images covering the Salt River/Mark Twain basin were obtained for five dates in the 2003 growing season: 26 May, 5 July, 22 August, 7 September, and 23 September (fig. 1). For complete coverage of the study area, it was necessary to combine Landsat scenes from row 32 and row 33 of path 25. For this research, the following 30-m resolution ETM+ bands were used: 0.45 to 0.52 μm (blue, band 1), 0.53 to 0.61 μm (green, band 2), 0.63 to 0.69 μm (red, band 3), 0.75 to 0.90 μm (near-infrared, NIR, band 4), 1.55 to 1.75 μm (short wavelength infrared, SWIR, band 5), and 2.10 to 2.35 μm (SWIR, band 7). The images were Level 1 geometrically corrected (L1G), meaning that they were systematically geo-rectified with a specific output map projection, image orientation, pixel grid-cell size, and resampling kernel. These five images were then combined to make a 30-band composite image (fig. 1). Coordinates of the combined Landsat image were adjusted to match the mosaicked USGS DOQQ image for the study area obtained from the Center for Agricultural, Resource, and Environmental Systems (CARES) at the University of Missouri. The 1:24,000 scale DOQQ provided a common base map for aligning all spatial datasets used in this study.

We did not apply atmospheric correction to the Landsat 7 images. Because the two scenes combined within each measurement date were sequential (i.e., subsequent rows in the same path), all data were obtained within 50 s and any effects of changing sun angle over that time were minimal. Visual examination of the images showed the atmospheric conditions to be homogeneous over the area of interest. Liang et al. (2002) stated that classification could be done without atmospheric correction under these conditions. Furthermore, our approach to combining multiple images into a single dataset was the same as that followed by Song et al. (2001), who stated that "atmospheric correction is unnecessary for change detection based on classification of multidate composite imagery in which multiple dates of remotely sensed images are rectified and placed in a single dataset, and then classified as if it were a single date image" (p. 232). Thus, we judged it unnecessary to atmospherically correct the images used in this study.

16-Day NDVI Images from MODIS

Twenty-three 16-day, 250-m NDVI products based on MODIS images, one from each subsequent 16-day period in 2003, were obtained from the Land Processes Distributed Active Archive Center maintained by the U.S. Geological Survey at http://lpdaac.usgs.gov/lpdaac/get_data. The MODIS NDVI product was calculated using the red (0.6 to 0.7 μm) and NIR (0.7 to 1.1 μm) wavelengths using the constraint view angle maximum value composite (CV-MVC) procedure (Heute et al., 1999). The 23 individual 16-day NDVI images were combined into a single composite image in ERDAS Imagine 8.7 (Leica Geosystems Geospatial Imaging, Norcross, Ga.). This one-year NDVI composite image was used to reflect seasonal trends in vegetation as a reference for crop type identification in the second classification method.

Ground-Truth Data

Accuracy assessment requires the availability of ground reference data, which are sometimes difficult and expensive to collect. It is an accepted practice that interpretations from large-scale aerial photographs can be used as surrogate reference data. In this study, 2-m color infrared aerial photographs of Missouri, imaged in 2003, were used as ground-truth data to identify forest, water, roads, bare soil, and built-up areas to be excluded from the crop type classification. These images were the same DOQQ described above.

Ground-truth data for 2003 crop type were obtained from the USDA Farm Service Agency (FSA) for the following counties in Missouri: Macon, Monroe, Randolph, Ralls, and Shelby. These five counties included 66% of the land area of the Salt River basin. The FSA data were joined to the USDA Common Land Unit (CLU) database to provide georeferenced field polygons with crop type as an attribute. The crop-type attributed CLU polygons were spatially adjusted to match coordinates of the CARES DOQQ images used as a base map. Ralls County data were used in the class identification process, while data from all counties were used for accuracy assessment.

Image Classification

The overall process of crop type differentiation included image classification and then class identification. The image classification step was identical for both methods, while the class identification step differed between methods. A process diagram describing the two methods is shown in figure 2.

The ISODATA method of USC was used to extract spectrally distinct classes from the combined Landsat image. The ISODATA algorithm is a more sophisticated variant of the general *k*-means algorithm and allows clusters to be merged and split during the iteration process (Tou and Gonzalez, 1974). In this study, 0.995 was used for a convergence threshold, meaning that classification was complete when the class values of 99.5% of image pixels were unchanged between subsequent iterations. To minimize the potential for a single ISODATA class to contain more than one crop type or land cover, a total of 150 classes were defined.

Although most recent land cover or crop type identification projects have used SC, some have also used USC (Cohen and Shoshany, 2002; Duda and Canty, 2002). In this research, we chose the USC approach because we needed to create historical crop type maps for watersheds where training data were limited and were available in only one portion of the watershed (the 2003 dataset available for this evaluation was a special case where data were available over most of the watershed area). We judged USC to be the better choice in this case because we were concerned that SC would not perform adequately with these limited, and potentially not completely representative, training data.

Class Identification

Method 1: Manual Class Identification Using FSA Crop Type Data

The 150 clusters in the USC image were grouped and labeled to crop type using FSA data from Ralls County for reference data. The clusters were visually checked to define the specific crop type in ERDAS Imagine 8.7 using the raster at–

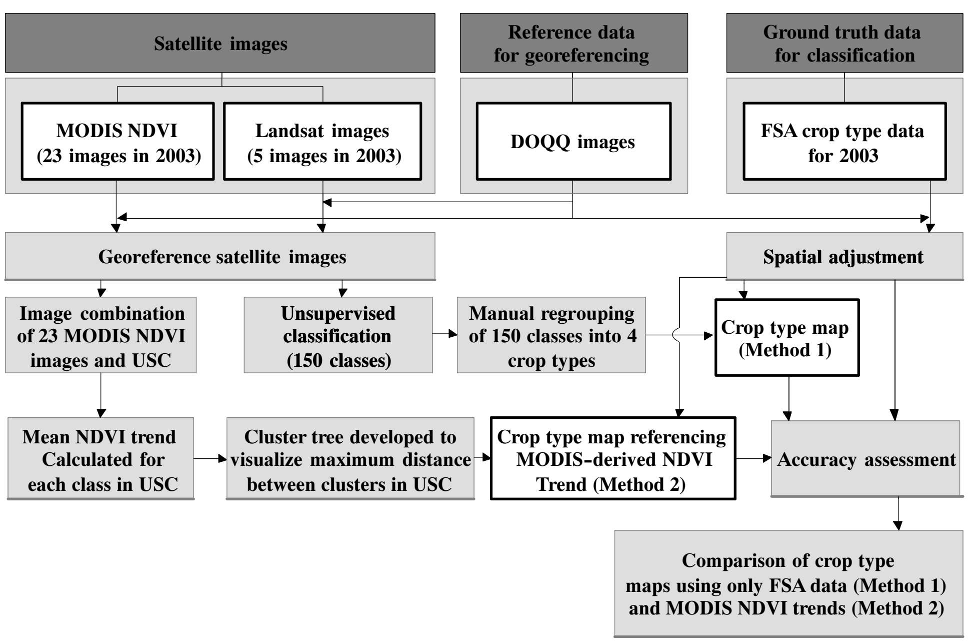

Figure 2. Overall process of image classification and class identification using manual identification (Method 1) and MODIS-derived NDVI data (Method 2).

tribute editor window. Clusters that corresponded to a single crop type in the FSA data were retained and labeled. The dominant crop type was determined for those non-homogeneous clusters containing two or more crops in the FSA data, and those clusters were labeled as the dominant crop type. The clusters that represented other land cover (e.g., forest, water, road, and built-up area) were clipped from the image. Finally, the clusters identified to crops were regrouped into classes representing the specific crops using the "recode" module in ERDAS Imagine.

Method 2: Class Identification from MODIS-Derived NDVI Trends

Method 2 also began with the 150 USC clusters derived from the Landsat images. MODIS-derived NDVI data were then used in a cluster tree analysis to group the 150 clusters according to crop type. The 250-m resolution MODIS images were first resampled to the 30-m resolution of the Landsat-derived USC image. Then, the pixels in the stack of MODIS NDVI images corresponding to each of the 150 USC clusters were extracted and a mean NDVI was determined for each of the 23 MODIS images in ERDAS Imagine. These mean NDVI data, consisting of a 23-date trend for each of the 150 Landsat-derived USC clusters, were output for subsequent analysis in SAS (version 8.2, SAS Institute, Inc., Cary, N.C.).

Ward's method (Ward, 1963) implemented in the CLUSTER procedure in SAS, was used to group the 150 USC classes based on the degree of similarity in their mean MODIS-derived NDVI trends. Ward's method is an agglomerative hierarchical clustering procedure that successively merges "nearest" clusters, where distance is based on a between-cluster sum of squares. A dendrogram, or tree diagram, was constructed with the TREE procedure in SAS to show the hierarchy of the clustering output, with those clusters with more similarity being more closely grouped at the base of the dendrogram. The ground-truth data corresponding to the branches of the dendrogram were used to identify which portions of the cluster tree represented specific crops plus an "other" land cover classification.

Accuracy Assessment

For accuracy assessment, Congalton (1991) suggested the rule of thumb that a minimum of 50 samples should be obtained in each land use/cover category to produce an error matrix. According to Van Genderen and Lock (1977), this implies a 95% interpretation accuracy level. In this study, the sampling unit used was the pixel, and over 1300 pixels were selected for accuracy assessment of the crop type map. Because there were relatively fewer fields of some crops, (e.g., wheat), the number of assessment samples for each crop varied.

The relationships between image classification and actual land cover were expressed using classification error matrices (Lillesand et al., 2004). This approach allowed easy visualization of errors of omission (i.e., pixels classified to another crop type) and errors of commission (i.e., extra pixels classified as a given crop type). It also quantified user's accuracy (i.e., the probability that a pixel classified as a given crop actually represented that crop on the ground) and producer's accuracy (i.e., the probability that pixels in the training set were classified correctly).

A separate error matrix was prepared for Ralls County data to document the accuracy of the classification processes in the same geographic area from which the ground-truth data used in the classification were obtained. Data from the other four counties were pooled in a common error matrix to provide an accuracy assessment for a portion of the basin that was independent of the ground-truth data used in the classification. Additionally, results from both methods were compared to county-level crop statistics (USDA-NASS, 2003).

Results and Discussion

Method 1: Manual Class Identification Using FSA Crop Type Data

Applying the manual class identification method, coupled with Ralls County ground-truth crop type data, to the ISODATA-classified image of the study area (fig. 3), it was possible to identify four crops: soybean, corn, grass (including CRP), and wheat (fig. 4). Unfortunately, it was not possible to reliably identify a categorization for grain sorghum because its temporal reflectance characteristics were similar to those of soybean (Wardlow et al., 2007) and because there were few sorghum fields in the Ralls County ground-truth dataset. These factors resulted in grain sorghum pixels being contained in classes where a majority of the class members were other crops, primarily soybean. We expected the effect on classification accuracy of other crops to be small, as grain sorghum was planted on only 4% of the cropped area, which was less than 6% of the area planted to soybean (USDA-NASS, 2003).

Accuracy assessment for Method 1 was based on 155 and 1266 randomly selected pixels from the crop fields in Ralls and the other four counties, respectively. The crop type defined in the Method 1 classification was compared to the crop type for that pixel from the FSA crop data. Ralls County, in the eastern part of the Salt River basin, was the same area from which the ground-truth data for class identification was taken, while data from the other four counties provided an independent accuracy assessment. Over both datasets, the accuracy of Method 1 was 83.0% and the kappa coefficient, which expresses the reduction in error generated by a classification process compared to the error of a completely random classification, was 0.76. In both the dataset for Ralls County (table 1) and the dataset for the other counties (table 2), overall accuracy levels were good, at 83.1% and 82.9%, respectively. These similar accuracy levels indicated that ground-truth data from the limited area of a single county could provide sufficient information to allow good classification over the entire basin. Accuracy levels were generally good, but varied for different crops, ranging from 75% to 90% for corn, 81% to 85% for soybean, and 78% to 80% for grass. Accuracy levels for wheat were more variable, ranging from 57% to 92%. The relatively smaller number of wheat fields evaluated in each dataset (tables 1 and 2) gave rise to more variability in the error statistics for wheat. As noted earlier, it was not possible to identify clusters that were primarily grain sorghum using Method 1.

Method 2: Class Identification from MODIS-Derived NDVI Trends

The cluster tree based on NDVI trends showing maximum distance between clusters is shown in figure 5. Considering

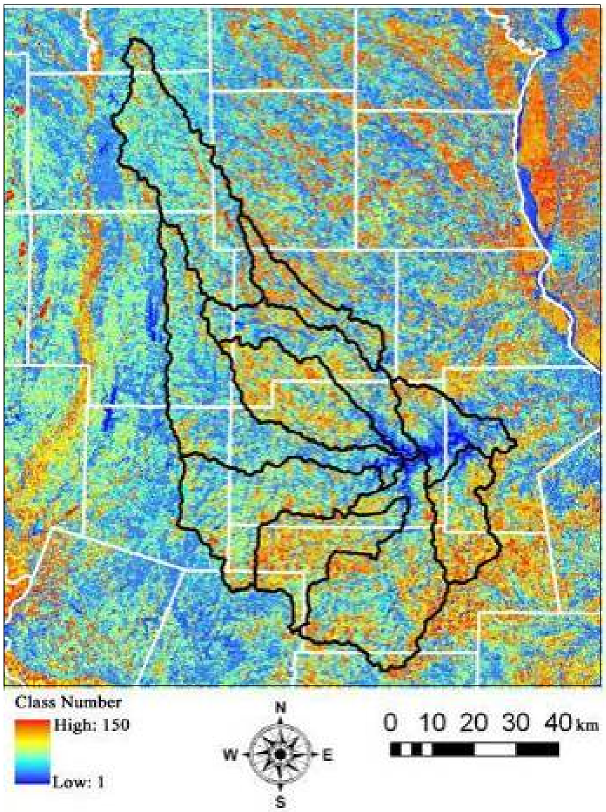

Figure 3. ISODATA-classified image of study area.

Table 1. Accuracy statistics for Ralls County crop type classification using Method 1.

	Soybean	Corn	Grass (CRP)	Wheat	Classified Total	User's Accuracy
Soybean	46	7	1	0	54	85.2%
Corn	3	27	0	0	30	90.0%
Grass (CRP)	3	2	43	1	49	87.8%
Wheat	4	0	5	12	21	57.1%
Reference total	56	36	49	13	154	
Producer's accuracy	82.1%	75.0%	87.8%	92.3%		83.1%

Table 2. Accuracy statistics for crop type classification in Shelby, Macon, Monroe, and Randolph Counties using Method 1.

	Soybean	Corn	Grass (CRP)	Wheat	Classified Total	User's Accuracy
Soybean	392	41	22	9	464	84.5%
Corn	39	247	1	6	293	84.3%
Grass (CRP)	35	21	246	14	316	77.8%
Wheat	17	7	4	165	193	85.5%
Reference total	483	316	273	194	1266	
Producer's accuracy	81.2%	78.2%	90.1%	85.1%		82.9%

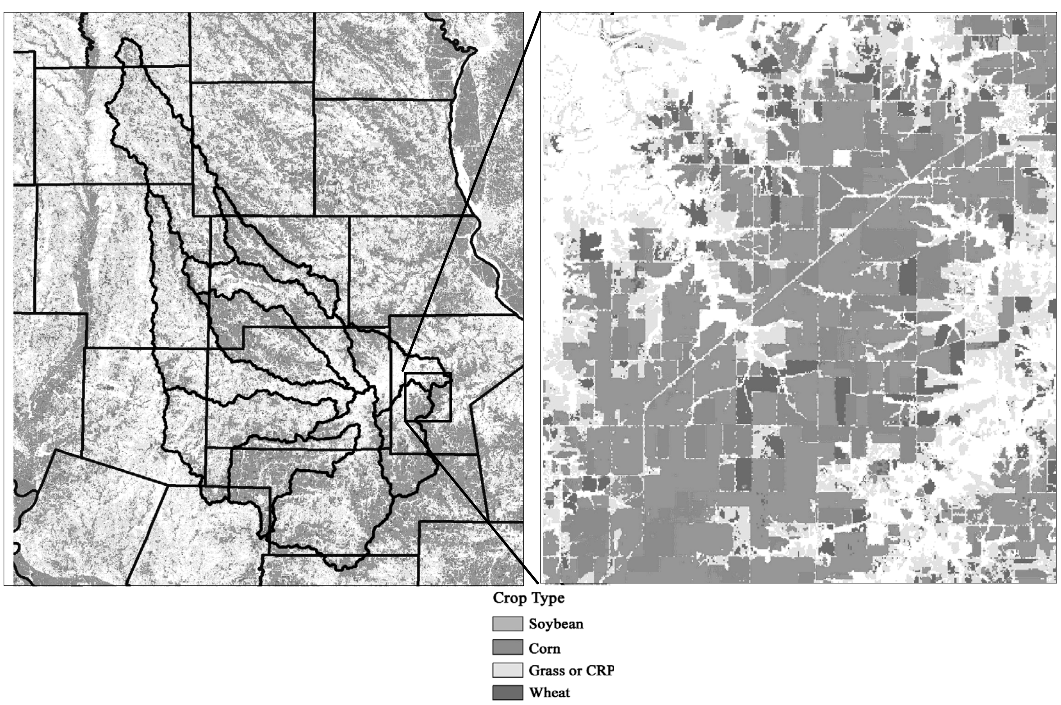

Figure 4. Crop type map obtained by Method 1. White areas denote non-cropped land use.

the hierarchical structure of the cluster tree, classes in each smallest cluster (at the lowest level of the tree) were compared on the basis of their NDVI trends. If the same trends were seen in all cluster members, then that cluster was identified to the appropriate crop type using the FSA ground-truth data. This process was repeated at successively higher levels of the tree until the level where cluster members were dissimilar in terms of NDVI trend. This resulted in several broadly defined clusters corresponding to the crop types of interest. The clusters having the same NDVI trend were iden–

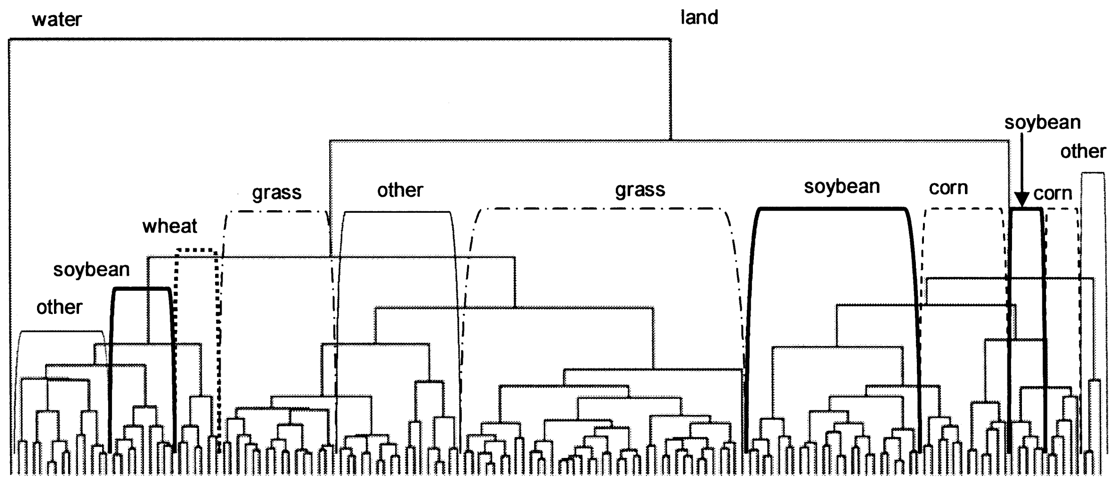

Figure 5. Cluster tree identifying crop types.

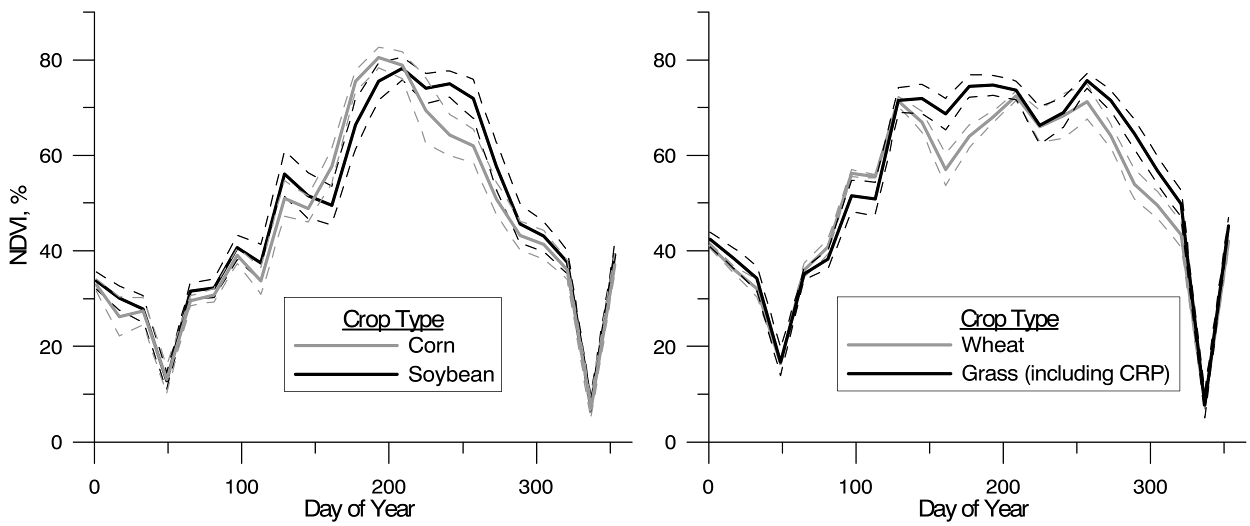

Figure 6. NDVI trends (mean ±1 standard deviation) for four identified crop types.

tified and grouped into the same crop, as well as an "other" category that represented non-cropped area (fig. 6). As with Method 1, it was not possible to identify a categorization for grain sorghum. Again, grain sorghum pixels were contained in classes where a majority of the class members were other crops, primarily soybean.

The crop for each class was re-identified using crop information in the FSA data, and NDVI trend graphs were grouped by crop type (fig. 6). Examination of these graphs revealed differences among crops. Soybean had a slightly longer period of peak NDVI (from approximately day of year [DOY] 190 to DOY 260) than corn. A secondary peak near DOY 130 may have been caused by emergence of weeds that were then removed by herbicide or tillage around the time of planting. Corn had a narrower and earlier peak in NDVI than soybean, along with a steep increase and decrease before and after the peak. NDVI remained high from DOY 130 to DOY 270 for grass, a longer period of peak NDVI than other crop types. Wheat had two main NDVI peaks near DOY 139 and DOY 210 with a short decrease in NDVI between them. The first peak represented the wheat NDVI before harvest, which occurred around DOY 180 in the study area, and the other peak was caused by other land cover, either double-cropped soybean or grass and weeds that appeared after the harvest of the wheat. A similar bimodal distribution in winter wheat NDVI was reported by Wardlow et al. (2007), who analyzed 2001 MODIS VI data from across the state of Kansas.

The crop information from cluster tree analysis was applied to the 150 Landsat-derived classes (fig. 3) to obtain the Method 2 crop type map (fig. 7). As with Method 1, four crops were mapped: soybean, corn, grass including CRP, and wheat. For accuracy assessment of Method 2, 132 and 1277 points were randomly extracted from the crop fields of Ralls County and the other four counties, respectively. Overall accuracy by Method 2 was 86.0%, better than the manual classification (Method 1) value of 83.0%. The kappa coefficient for Method 2 was 0.81, again better than the 0.76 calculated for Method 1. In the Method 2 error matrices for both Ralls County (table 3) and for the other four counties (table 4), overall accuracy levels were higher than for Method 1, at 88.6% and 85.7%, respectively. In most cases, accuracy levels for individual crops were also better for Method 2 than for Method 1.

Crop Area Estimation

Crop area statistics from Method 1 and Method 2 were compared to NASS data (USDA-NASS, 2003) for nine counties within or partially within the Salt River basin. Linear re-

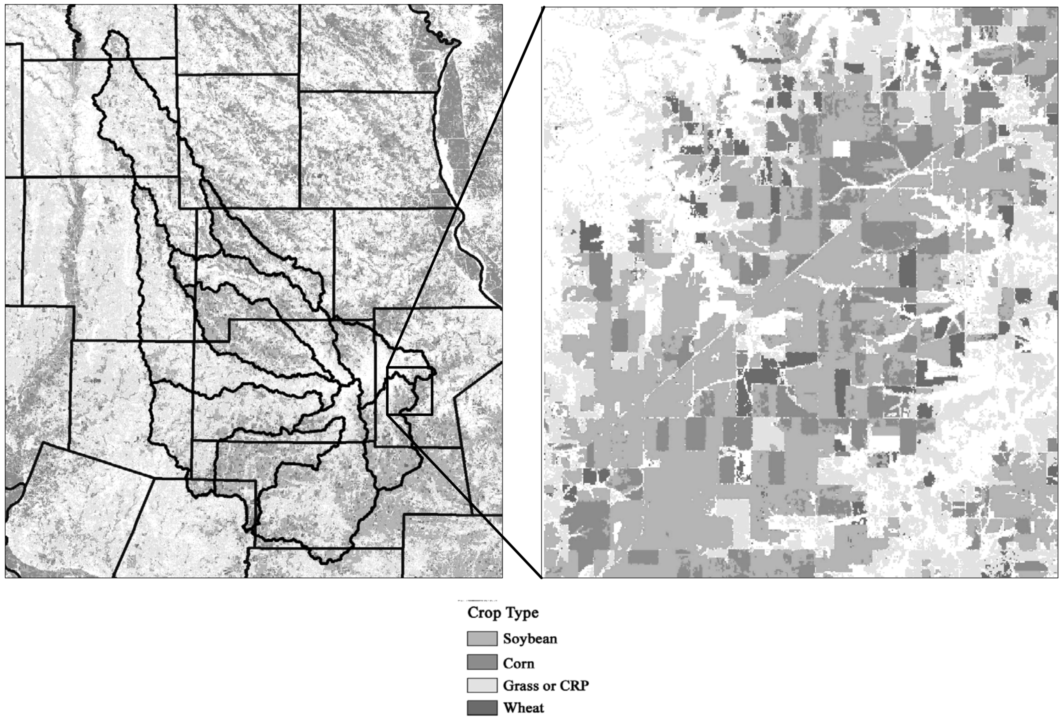

Figure 7. Crop type map obtained by Method 2. White areas denote non-cropped land use.

Table 3. Accuracy statistics for Ralls County crop type classification using Method 2.

	Soybean	Corn	Grass (CRP)	Wheat	Classified Total	User's Accuracy
Soybean	54	7	0	0	61	88.5%
Corn	0	29	0	0	29	100.0%
Grass (CRP)	0	1	26	5	32	81.3%
Wheat	1	1	0	8	10	80.0%
Reference total	55	38	26	13	132	
Producer's accuracy	98.2%	76.3%	100.0%	61.5%		88.6%

Table 4. Accuracy statistics for crop type classification in Shelby, Macon, Monroe, and Randolph Counties using Method 2.

	Soybean	Corn	Grass (CRP)	Wheat	Classified Total	User's Accuracy
Soybean	411	55	3	6	475	86.5%
Corn	18	255	5	3	281	90.7%
Grass (CRP)	24	17	258	24	323	79.9%
Wheat	23	4	0	171	198	86.4%
Reference total	476	331	266	204	1277	
Producer's accuracy	86.3%	77.0%	97.0%	83.8%		85.7%

gression fits between Method 1 data and NASS data were very good, with r^2 values of over 0.9 for both corn and soybean and estimates very close to the 1:1 line (fig. 8). Corn and soybean area estimates by Method 2 were slightly worse, with r^2 values of 0.85 or better. Method 2 tended to overestimate soybean area by up to 20% and to underestimate corn area by a similar amount. This may be explained by the fact that, in the Method 2 accuracy assessment described above, errors of omission were more prevalent for corn while errors of commission were more prevalent for soybean (tables 3 and 4). In contrast, the two types of error occurred more evenly for Method 1 (tables 1 and 2). Area estimates for wheat were very good by Method 2, but not as good by Method 1. Correspondingly, user's accuracy was higher for wheat with Method 2 (tables 3 and 4) than with Method 1 (tables 1 and 2). The relatively small number of wheat fields in the training sample likely made the manual identification operation difficult in Method 1, while the NDVI-trend method may have been better able to represent the range of conditions seen in wheat fields, thus providing a more accurate classification. Further study would be required to ascertain if Method 2 would consistently perform better for small training samples. Because NASS data only report grasslands that are harvested as hay, the remote-sensing derived grass areas were much higher than those from NASS. However, there was still a strong linear relationship between the two measurements.

Comparing the two methods, the MODIS NDVI-derived crop type map (Method 2) had higher accuracy than the manually identified crop type map (Method 1). Differences between the methods were especially apparent for wheat, which had relatively fewer fields in the training sample. This may be an indication that Method 2 can provide better results with less training data; however, this would need to be verified with additional datasets. The overall process using Method 2 was also more efficient, allowing classification of crop types with limited ground-truth data. Method 1 required more reference ground-truth data and approximately twice as much manual interaction with the data than Method 2, and therefore was more time-consuming in categorizing crop types. In addition, because of the additional manual processes and subjective determinations involved in Method 1, Method 2 was expected to provide more repeatable results.

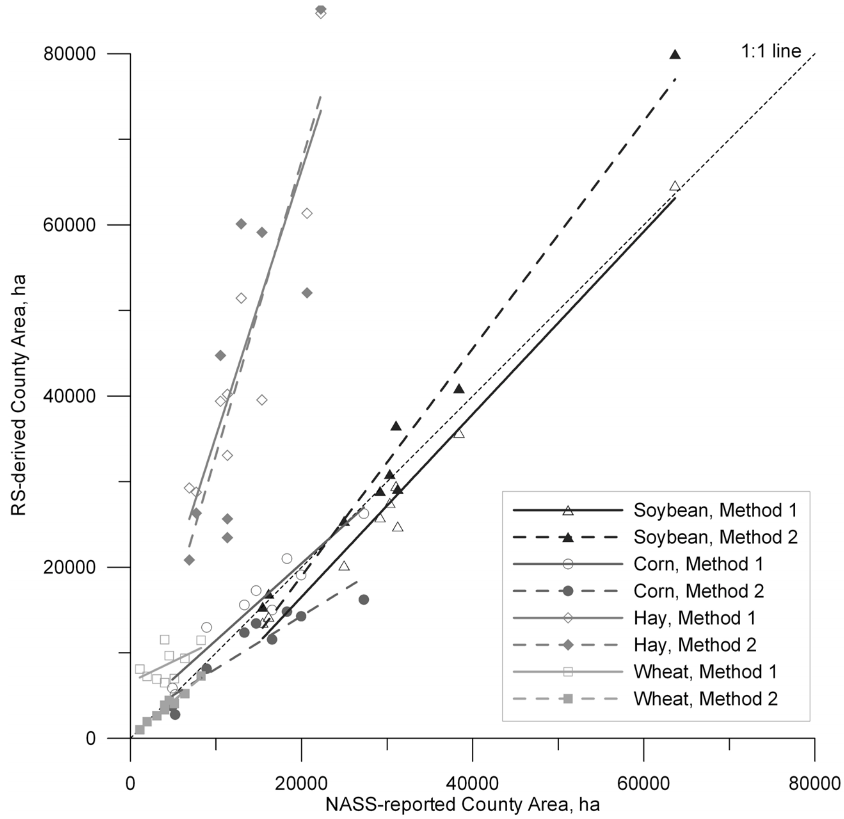

Figure 8. Comparison of county-level crop area from remote sensing estimates to those reported by USDA-NASS for nine counties within the Salt River basin.

Summary and Conclusions

The procedures developed in this study enabled the use of MODIS NDVI images as auxiliary data for Landsat-based differentiation of crop types. The seasonal trend information provided by the MODIS images improved the overall accuracy of the crop type map to 86%, compared with an 83% accuracy for the crop type map derived from a more conventional manual classification method using the ISODATA algorithm that did not incorporate MODIS seasonal trend data. This better accuracy, coupled with higher efficiency and better repeatability in the classification process, leads us to recommend the MODIS-assisted method for crop type determination.

Accuracy levels were similar for the dataset from Ralls County (location of ground-truth) and that from the other four sampled counties, indicating that both classification procedures could be used across the entire 6,520 km^2 basin even though ground-truth data were obtained in a smaller area. This is an important finding, as ground-truth data are often difficult to obtain over wide areas. There would likely be a limit to the geographic range of applicability of such ground-truthing, because important factors such as soils, climate, and cropping patterns generally become more divergent with distance. However, we did not reach that distance in this study, where the maximum distance between sampled ground-truth locations was approximately 100 km.

Corn was well discriminated from the other crops, with a user's accuracy of 84% or better for Method 1 and 90% or better for Method 2. This is important because the fertilizer (nitrogen) and herbicide (atrazine) mainly used in corn production are two major interests in watershed modeling efforts, and this level of discrimination should allow accurate estimation of corn fertilizer and herbicide inputs.

A problem with both methods was their inability to differentiate grain sorghum from other crop classes, with most grain sorghum fields being incorrectly classified as soybean. This may have been because the area with ground-truth data had relatively few grain sorghum fields, and because the temporal growth pattern and NDVI signature of grain sorghum are similar to soybean. Correctly differentiating between soybean and grain sorghum is highly desirable because very different crop chemicals are used with the two crops. Future work should address this issue, perhaps using ground-truth data from an area where grain sorghum is a more predominant crop.

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